Agent-Based Modeling of Resource Allocation in Software Projects Based on Personality and Skill

Abstract. The success or failure of software development group work depends on the group members' personalities, as well as their skills in performing various tasks associated with the project. Normally the project managers are responsible for forming a group by selecting the appropriate members to form a team in order to solve a particular problem. In this study, we explore the impact of different personalities and the interrelationships between various personalities that make up a group that works together as a team towards completing a particular task. Assigning appropriate employees is beyond the personality composition and skill competency of employees. In the reality, tasks have a dynamic nature and their requirements change over time. Therefore, we study the effect of task dynamics on the teamwork. To do so, after describing a general approach to select effective team members, we consider as an example a comparative multi-agent simulation study contrasting two different sample strategies that managers could use to select team members: by minimizing team over-competency and by minimizing team under-competency. Based on the simulation results, we drive a set of propositions about the conditions under which there are and are not performance benefits from employing a particular strategy for task allocation.

Keywords: Software teams, personality, skill, task allocation, dynamic tasks, agent-based simulation, team management

1 INTRODUCTION

Teamwork is an essential aspect of organizational work, and there have been a number of investigations into team composition and personality [1][2]. However, these studies have produced inconsistent results mainly because of two main constraints: firstly, they mostly consider the individual aspects of employees without fully covering group factors such as cohesion, conflict, team structure and coordination. Secondly they have not considered the dynamic nature of the task in conjunction with member personalities. In reality, various aspects of task dynamics such as changes in the task requirements or interdependency level for each task affect the team effectiveness.

Wood [3] argued changes in the complexity of tasks have an effect on the relationship between task inputs and products. Zoethout et al. [4] studied the influence on task variety on the behavior of specialists and generalists. Jiang et al. [5] examined how the change in task requirement dynamically affects individual behavior. In these studies, the relationship between managers' strategies in team formation and changes in the task requirement on the team performance is not fully covered.

adfa, p. 1, 2011.

Regarding these issues, in this paper, we have two main contributions. Firstly a team formation model is developed to calculate team formation performance based on personality composition and skills competency.

Secondly, we examine the relationship between the dynamic nature of tasks and managers' strategies for task allocation by using computer simulation. We model the evolution of task performance in terms of two types of parameters: task requirements and the personality distribution of employees. The simulation results can support managers' decision-making with respect to task allocation.

The outline of the paper is organized as follows: Firstly, based on reviewing the literature, we develop a computational model to evaluate the performance of software project teams based on skill competency in conjunction with personality composition of teams. The conceptual foundations and formal considerations of task allocation mechanisms are described. To demonstrate the application of the model, simulation studies are then presented. The simulation outputs compare two task allocation models in different tasks with different level of changes in their requirements. In addition, we study the relationship between employees' personality and different task allocation strategies.

2 Team formation mechanism in software projects

In order to make rules for forming software project teams, several studies that have tried to incorporate social psychology factors for building teams [1,6]. Among them, there is widespread recognition of the role of Myers-Briggs Type Indicator (MBTI) [7] and Belbin Team Roles (BTRs) [8] with respect to team performance.

2.1 MBTI and Belbin Team Roles

Myers [9] extended Jung psychological type [10], and it has evolved into what is now referred to as the Myers-Briggs Type Indicator (MBTI) scheme [7], which has four "dimensions" of human personality:

- Introversion vs. Extraversion (I-E) – the degree to which one faces the outer social world or keeps more to himself or herself.
- iNtuition vs. Sensing (N-S)– the degree to which one gathers information that is in concrete, objective form or is more abstract and understood according to one's inner compass.
- Thinking vs. Feeling (T-F) – the degree to which one makes decisions based on logic and demonstrable rationality or is more empathic and attempts to see things from given social perspectives.

- Perceptive vs. Judgmental (P-J) – the degree to which one wants to come to quick, categorical decisions or is more inclined to withhold judgment for the time being.

Belbin [8] introduced a theory about the roles of individuals in a team. In each team, every member has a role that might affect the performance of the team. In an early publication, eight team roles were identified: Chairman, Shaper, Plant, Monitor-Evaluator, Company Worker, Resource Investigator, Team Worker, and Completer-Finisher [4]. Later he added a ninth role, Specialist and renamed the Chairman to Coordinator and the Company Worker to Implementer [11]. Other researchers then raised the possibility that the relationship could be found between the MBTI. These roles are explained in Table 1 [8].

Table 1. Belbin Roles

Team Role	Contribution	Allowable weakness
Plant	Creative	Ignores incidentals.
Resource Investigator	Outgoing, Enthusiastic.	Over-optimistic.
Coordinator	Mature, Confidant.	Can be seen as manipulative.
Shaper	Challenging, Dynamic	Prone to provocation.
Monitor Evaluator	Sober, Strategic.	Lacks drive to inspire others.
Team Worker	Cooperative.	Indecisive in crunch situations.
Implementer	Practical.	Somewhat inflexible.
Completer	Painstaking.	Inclined to worry unduly.
Specialist	Single-minded.	Contributes only on a narrow front.

Personality profiles and Belbin Team Roles (BTRs) suggest that personality and role tendencies are not independent [12]. Stevens and Henry [13] tried to map these two instruments [14], Stevens [13] noticed that there is a different distribution of both BTRs and MBTI and from this distribution the personality related to the team roles could be determined, and Schoenhoff [15] continued this work by using a larger sample.

Myers also introduced a theory, namely MTR-i [16], which incorporates the idea of team roles, and he claimed people with different personalities are likely to have specifically correlated roles in a team. Table 2 compares the results of different studies (where X means no relationship between personality and Belbin role is found). The rightmost column of Table 2 indicates the degree of commonality among the other four studies. We designate the agreement points for that rightmost column if, for a given Belbin role, at least two of the studies agree on an MBTI personality dimension for that role. Also, these agreement points seem to be in relative accord with the Keirsey study of temperaments [17].

Table 2. Studies about the relationship of personality and BTRs

Belbin roles [8]	Henley report [18]	Stevens report [13]	Schoenhoff report [15]	MTR-I [16]	Agreement points
Coordinator	EXXX	XSXX	ENFP	ESFP/ESTP	EXFP
Shaper	EXXX	EXXX	XSTJ	ESFP/ESTP	ESTX
Plant	IXTX	XNTP	INTJ	INTJ/INFJ	INTJ
Monitor Evaluator	IXTX	XXXX	ISXJ	ISTJ/ISFJ	ISTJ
Implementer	XXXX	XSXJ	ISXJ	XXXX	XSXJ
Resource Investigator	EXXX	EXXP	ENFJ	ENTP/ENFP	ENFP
Team Worker	EXXX	XXXX	ISTJ	ESFJ/ENFJ	ESXJ
Completer	IXXX	XSXJ	ISTJ	XXXX	ISXJ
Specialist	XXXX	XXXX	XXXX	ISTP/INTP	XXXX

3 Performance calculation model

In this paper, we formulate a performance computation mechanism for software development projects by taking into consideration employees' personalities and skills. The motivation for the computational model is based on the previous findings and from both MBTI and BTR studies.

Belbin suggests two main factors for forming a team: dyadic relationships of team members and competency of team members in the tasks [8]. In this connection, we describe a formal model that represents the assignment of people to the software projects and which reflects the literature about team formation. Managers calculate the performance of each team composition and select the best one for their task. The general formula for calculation of team performance is expressed as follows.

$$Performance = \text{Personality\_}Composition * Competency \qquad (1)$$

$$Personality\_composition = (\text{c1} * Matching\_Personality + \text{c2} * Matching\_roles + \text{c3} * Creativity\_capability + \text{c4} * Urgency\_capability + \text{c5} * Sociality\_\ capability + \text{c6} * Complexity\_capability + \text{c7} * \text{Belbin\_}Creativity\_\ capability + \text{c8} * \text{Belbin\_}Urgency\_capability + \text{c9} * \text{Belbin\_}Sociality\_\ capability + \text{c10} * \text{Belbin\_}Complexity\_capability)$$
(2)

To express this more compactly, we can write this as

$$Performance = (c_1*Pm + c_2*Rm + c_3*Cr + c_4*Um + c_5*So + c_6*Co + c_7*Bcr + c_8*Bum + c_9*Bso + c_{10}*Bco) * c_{11}*C \quad (3)$$

The various parameters, such as *Matching_personality,* (*Pm*)*, Matching_roles (Mr) ,…, C (Competency)* are explained and formulated in the next sections. These variables are numerical values that can be uniformly taken to be measured along some scale, such 0 to 1 and each one explained in the following sections. The identifiers c1, …, c11 are coefficients that can be adjusted for fitting empirical measurements. In this formulation for team performance, we have considered the factors that were most prevalent from our literature survey. Further variables of our model are described as follows:

- m: the number of skills required for tasks
- n: the number of employees for each team
- R_k: the skills requirement vector for task k. Thus $R_k = [R_{k1}, R_{k2} \ldots, R_{km}]$
- im: an index identifier indicating the most important skill
- $R_k[im]$: the skill requirement of the most important skill for the task k.
- S_i: the skills vector of employee i. $S_i = [S_{i1}, S_{i2}, \ldots, S_{im}]$

These parameters are based on our literature survey, and we provide further descriptions of these factors in the following. We describe skill competency and personality composition that are mentioned in formula 1 as follows:

3.1 Skill Competency of team members (C)

An important factor is the competency or skills of the team. We calculate the competency for each skill by dividing the skill of an employee by the skill requirements for the task. The overall team competency is the sum of all the team members' competencies for each skill.

In practice, managers have various preferences for task allocation. The standard approach is to find the minimal difference between the skills of employees and the task demands, and it is used in different ways in the literature for personnel selection [25]. However, existing methods have not considered a positive and negative gap values in connection with the differences. In our model, we propose a similarity measure such that a positive gap value is considered as over-competency and a negative value is considered as under-competency. These two methods are presented as two different task allocation strategies. For each strategy, the manager will calculate a utility skill competency of team and choose teams with the highest value.

3.1.1 Minimizing Under-competency

In this method, the main purpose of the manager is minimizing under-competency in assigning the task to the employees. They try to choose the best combinations of employees who have the least under competency in their skill. So they calculate the utility of teams based on the following formula. Where C_{il} represents the competency of employees in the skill in this mechanism, R_l represents the skill requirement of task l, and S_{il} represents the skill of employee i in task l.

$$C_{il} = 1 - \max(\,0,\ (R_l - S_{il})/R_l\,) \tag{4}$$

3.1.2 Minimizing Over-competency

In this method, the main purpose of the manager is minimizing over-competency in assigning the task to the employees. They try to choose the best combinations of employees who have the least over competency in their skill. So they calculate the utility of teams based on the following formula. Where C_{il} represents the competency of employees in skill in this mechanism.

$$C_{il} = \begin{cases} 1 - \frac{(S_{il} - R_l)}{R_l} & if\ \ S_{il} - R_l \geq 0 \\ 1 - \frac{(R_l - S_{il})}{R_l} & if\ \ S_{il} - R_j < 0 \end{cases} \tag{5}$$

3.2 Personality Composition

The first ten factors in Formula (3) are related to the personalities of team members. We measure the goodness of team composition by factors such as matching their Belbin's roles, matching their MBTI Personality, team creativity, the MBTI capability of team to dealing with task requirements such as creativity, urgency, sociality, and task complexity, and the Belbin capability of the team to deal with task requirements such as creativity, urgency, sociality and task complexity. Each factor is described as follows:

Matching_roles (Rm) : Matching roles represents the degree to which Belbin roles are suitably matched. All the people have a primary natural team role that affects their behavior with each other. The interactive relationships of team members influence the team environment and performance. For example, if someone is aggressive towards someone, the recipient may respond by being diplomatic or by having a significant clash with the aggressor. Belbin's study shows this interpersonal relationship and what kind of people have likely conflict with each other and what kind of people tend to work well with each other. In Table 3, we summarize these interpersonal relationships from Belbin's work [8].

On the basis of these relationships, we formulate the index *Rm* as an indication of relationship compatibility:

$$Rm_b = \frac{(Ps_b - Pu_b\,)}{\max[Ps_b\,, Pu_b]} \tag{6}$$

Where Rm_b is the degree of matching of peers' roles in team b, Ps_b is the number of suitable roles in the team, and Pu_b is the number of unsuitable roles in the team.

Table 3. Belbin's roles

Role	Suitable Peer	Unsuitable peer
Shaper	Resources investigators	Plant
Specialist	Implementers, Team Workers	Plant
Monitor Evaluator	Coordinators, Implementers	Completers, Other Monitor Evaluators
Completer	Implementers	Resource Investigators
Implementer	Coordinators, Monitor Evaluators, Resource Investigators, Completers and Specialists	Other Implementers and plants
Resource Investigator	Implementers and Team Workers	Completers and Specialists
Coordinator	Implementers and Team Workers	Shapers
Team Worker	other Team Workers and Plants	Shapers

Matching_index (Pm) : Matching-index (Pm) represents the degree to which personalities, as measured by MBTI type, are matched. We base this on studies about the effect of personality composition of a team. As with Belbin's roles, some personalities do not get along well with each other, so it can be important to configure team personalities appropriately. We have surveyed the literature concerning personality composition of teams, and Table 4 shows the relationship conflicts across MBTI personality types. These assumptions are based on [19,20,21,22,23].

Table 4. Relationships of MBTI personality dimensions

	T	F
T	0	+
F	+	0

	J	P
J	+	-
P	-	+

	E	I
E	-	0
I	0	0

	S	N
S	0	+
N	+	0

Note that in the table, '+' means that there is a positive effect, '-' means there is a negative effect, and '0' means that there is no effect.

It has been found, for example that two extraverted people working together can be problematic because they can be dominant and assertive towards each other. Additionally, it has been found that Sensing and iNtution types can be useful to each other, as well as Feeling and Thinking. People who differ across the Judging and Perceiving dimension tend to frustrate each other, but people at the same end of the

Judging or Perceiving scales have similar interests and can understand and predict each other's behavior.

For each of the four MBTI personality dimensions, we established a scale between 0 and 100 and assigned values for each employee.

- Introverted/Extraverted: (range 0-50 → *Introverted*; 50-100 → E*xtraverted*).
- Intuitive/Sensing: (range 0-50 → *Intuitive;* 50-100 → S*ensor*),
- Thinking/Feeling: (range 0-50 → *Feeler;* 50-100 → *Thinker*),
- Perceiving/Judging: (range 0-50 → *Perceiver;* 50-100 → J*udgers*).

Using these parameters, we construct the final score for matching personality as:

$$Pm_b = \frac{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} EE_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{n} SN_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{n} TF_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{n} JP_{ij}\right)}{4} \qquad (7)$$

In the above, EE_{ij} represents the dyadic effect of the Extraverted-Introverted dimension (in this case introversion has no effect), SN_{ij} represent the dyadic effect of the Sensing-Intuition dimension, TF_{ij} represents the dyadic effect of the Thinking-Feeling dimension, and JP_{ij} represents the dyadic effect of the Judging-Perceiving dimension. Pm_b indicates the matching personality of team b.

So far, we have just considered how personalities and roles match with each other, but we must also take into consideration how they match up with the task types. To operationalize this, we consider various tasks to have different levels with respect to (a) required creativity, (b) urgency, (c) required social interaction, and (d) complexity. Each of these categories is discussed further below. In this connection, we use two additional indicators that are useful for these considerations [24]:

- Team Personality Elevation (TPE): a team's mean level for given personality trait.
- Team Personality Diversity (TPD): the variance with respect to a personality trait

Creativity (Cr): For tasks requiring a high level of creativity, teams composed of differing attitude tendencies are believed to perform better than teams of like-minded people [24]. So, here we assume high heterogeneity (high TPD) in the four personality dimensions will lead to creativity. Moreover, the creativity of individuals is related to their Intuition level [21]. So in addition to a high TPD in all four personality dimensions, we also assume that high TPE in Intuition has positive effects on creativity. In the following expressions, Cri_b is the combined team index for creativity, and Crr_k is the required creativity for the task.

$$Cr_b = (TPE \text{ of } Intuition + mean\ of\ TPDs\ )/\ n * 100) \qquad (8)$$

$$Cri_b = \begin{cases} Cr_b/Crr_k & if\ \ Crr_k - Cr_b \geq 0 \\ 1 & if\ \ Cr_b - Crr_k > 0 \end{cases} \qquad (9)$$

Urgency ($\boldsymbol{Um}$): When time is important, Perceiver types, who need freedom for their actions, are less likely to be successful. In contrast, Judgers relish getting in on the closure of a task, and so they can have a positive effect on tasks with time pressure. As a result, we believe that a high TPE in Judging has a positive effect in performing urgent tasks.

$$Um_b = \ TPE\ in\ Judgers\ /\ n\ *\ 100 \tag{10}$$

$$Umi_b = \begin{cases} Um_b/Umr_k & if\ \ Umr_k - Um_b \geq 0 \\ 1 & if\ \ Um_b - Umr_k > 0 \end{cases} \tag{11}$$

Umi_b is the combined team score (index) for Urgency, and Umr_k is the required Urgency for the task.

Sociality ($\boldsymbol{So}$): For tasks involving many social interactions, extraverted individuals can help the team. Therefore, we assume a high TPE in Extraversion has a positive effect in performing these tasks.

$$So_b \ = \ TPE\ in\ extraverted/n\ *\ 100 \tag{12}$$

$$Soi = \begin{cases} So_b/Sor_k & if\ \ Sor_k - So_b \geq 0 \\ 1 & if\ \ So_b - Sor_k > 0 \end{cases} \tag{13}$$

Soi_b is the combined team is score for Sociality, and Sor_k is the required sociality for the task.

Complexity ($\boldsymbol{Co}$): When the complexity of a task is high, a rational and scientific mind that is characteristic of thinking types can be useful. As a result, we expect a high TPE in Thinking will have a positive effect in performing these tasks.

$$Co_b \ = \ TPE\ in\ Thinking\ /\ n\ *\ 100 \tag{14}$$

$$Coi_b = \begin{cases} Co_b/Cor\ _k & if\ \ Cor_k - Co_b \geq 0 \\ 1 & \quad\ \ Co_b - Cor_k > 0 \end{cases} \tag{15}$$

Coi_b is the combined team score for complexity, and Cor_k is complexity of the task.

In addition to the above eight indicators, we assume that some roles are crucial for some tasks, so we have introduced the following constraints based on Belbin's findings [11]. Having

- at least one Plant is essential in teams with a high creativity requirement.
- at least one Completer is essential in teams with a high urgency requirement.
- at least one Evaluator is essential in teams with a high complexity requirement.
- at least one Resource Investigator is essential in teams with a high complexity requirement.

These rules are mathematically expressed in our model as follows:

$$Bcri_b = \begin{cases} 0 \quad if \;\; Crr_k > 50 \; and \; Plant \notin role_b \\ 0.25 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{16}$$

$$Bumi_b = \begin{cases} 0 \quad if \;\; Umr_k > 50 \; and \; Completer \notin role_b \\ 0.25 \qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{17}$$

$$Bsoi_b = \begin{cases} 0 \qquad if \;\; Sor_k > 50 \; and \; RI \notin role_b \\ 0.25 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{18}$$

$$Bcoi_b = \begin{cases} 0 \; if \;\; Cor_k > 50 \; and \; Evaluator \notin role_b \\ 0.25 \qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{19}$$

$Bcri_b$,$Bumi_b$, $Bsoi_b$, $Bcoi_b$ indicate the Belbin creativity, Belbin Urgency, Belbin Sociality, and Belbin complexity indices, respectively. And $role_b$ represents the role of all the members in team b. Crr_k, Umr_k, Sor_k, cor_k indicates the task requirement for creativity, urgency, sociality and complexity respectively.

4 SIMULATION AND RESULTS ANALYSIS

In order to explore the effect of task dynamics of our model on the proposed task allocation mechanism, we conducted some simulation experiments on the NetLogo platform [26].

In this model that is depicted in figure 1, the dynamic tasks are characterized by changing the requirements of tasks. In the reality, managers have to reschedule their projects because of new requirements for tasks. Rescheduling has some cost since it takes time for new member to be familiar with the new tasks, and it causes some dissatisfaction for those who leave the task. In each time step, with a certain probability, the requirements of one skill increase and managers select the best team for this task. So, in each time step managers calculate the payoff of changing teams, and if this payoff is positive, they change the team. This payoff is calculated by the following formula:

$$Payoff = \left(\sum_{i=1}^{n} C_{inew} - C_e t \right) - \sum_{i=1}^{n} C_{icurrent} \tag{20}$$

Where C_{inew} and $C_{icurrent}$ represents the competency of new and current team members respectively.

The cost of changing a team is a constant number and is indicated by C_e. The cost, of changing the current team, is formulated by $C_e t$. This cost is related to the time that has elapsed from the starting point of the project. As a result, the skill competency of team is calculated according to the following formula.

$$Ds_{bk} = \begin{cases} \sum_{i=1}^{n} C_{inew} - C_e t & if \ \left(\sum_{i=1}^{n} C_{inew} - C_e t\right) > \sum_{i=1}^{n} C_{icurrent} \\ \sum_{i=1}^{n} C_{icurrent} & if \ \left(\sum_{i=1}^{n} C_{inew} - C_e t\right) \leq \sum_{i=1}^{n} C_{icurrent} \end{cases} \quad (21)$$

$$Performance(t) = Ds_{bk} * Personality\_Composition_b * t \quad (22)$$

Where $Performance(t)$ indicates the performance of team in time t, $Composition_b$ indicates the personality composition of team b and calculated as presented in the formula 2. C_{il} indicates the competency of agent i in discipline l and C_b presents the competency of members in task b.

The experiments, we compare the performances of two managers who assign the employees to the tasks. In order to calculate the competency C_k, the manager with "Minimizing Under-competency" strategy uses Formula (4) and the manager with "Minimizing Over-competency" strategy uses Formula (5).

In the initial settings, the environment had 12 employees and four tasks. Both tasks and employees have some initial properties. In this connection, a task role is assigned to each person, and the choice for this role is guided by the personality information from Agreement Points (right-hand-most) column of Table 1. Values between 0 and 10 are assigned to the employees (these skills levels are assigned according to a normal distribution with a standard deviation of 3). In addition, specific task attributes are assigned to the task, such as the required level of creativity, social interactions, complexity, and urgency. A number between 0 and 100 is assigned to each such task attribute. Three skills are allocated to the task representing the skills that are required, and a number between 0 and 10 represents the required skill level. For the sake of simplicity, we assume that all teams comprise a small number (three) of employees. Also in the simulation settings, number 1 is assigned to $C1, \ldots, C11$.

The results of simulation experiments are summarized in Figure 2. It compares the simulation results of the two task allocation methods with different probabilities of increasing the task requirements in each time step. The results are averaged over 100 runs of the model.

The results revealed that by increasing the chance of changes in the task requirements, the performance decreases for both task allocation mechanisms. In the beginning, when the dynamic level of tasks is not significant, the under-competency mechanism outperforms the over-competency mechanism. However, after increases in the dynamic level of tasks, the over-competency mechanism ended up with a better performance compared to the under-competency mechanism. This phenomenon illustrates some interesting features, such as the importance of employing task allocation mechanism regarding the characteristics of the tasks and environment.

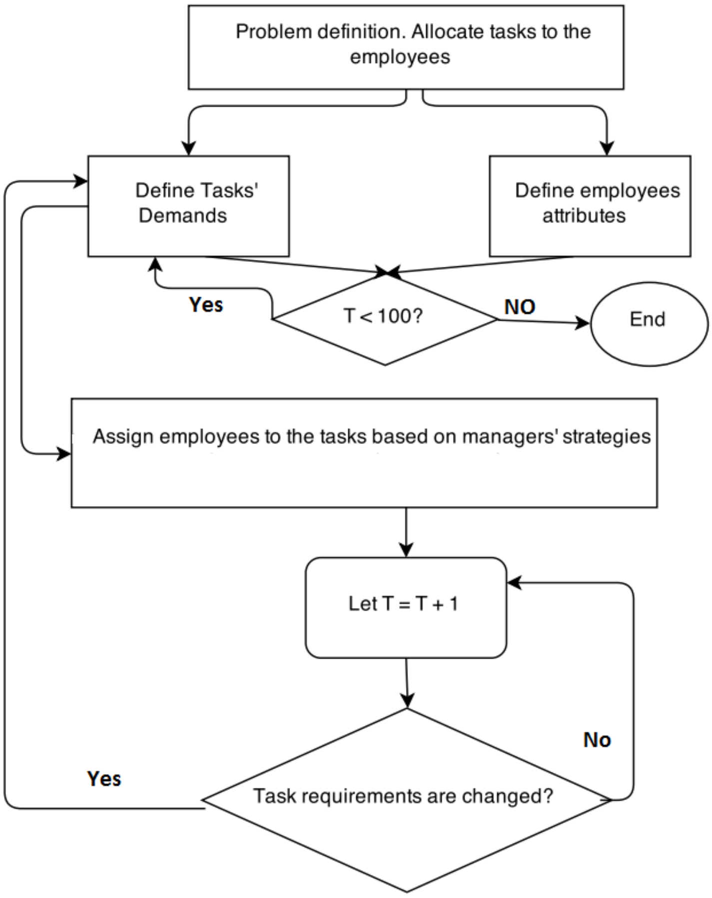

Fig. 1. Task allocation diagram

A simple, approximate explanation of this behavior is as follows: first, in the world when the probability of changes in the task requirement is small, managers who minimize over competency are more likely to make mistakes. For instance, among two employees that one is overqualified, and another one is underqualified over-competency managers might choose the underqualified one that will result in the poor performance. When this probability increases, the managers who minimize under competency make more mistakes. It occurs since the employee selection among some overqualified employees is a random process for these managers. For performing the next projects, they might want to assign these overqualified workers to tasks that are really required. This phenomenon occurs more in a dynamic environment and results in some costs for the under-competency managers.

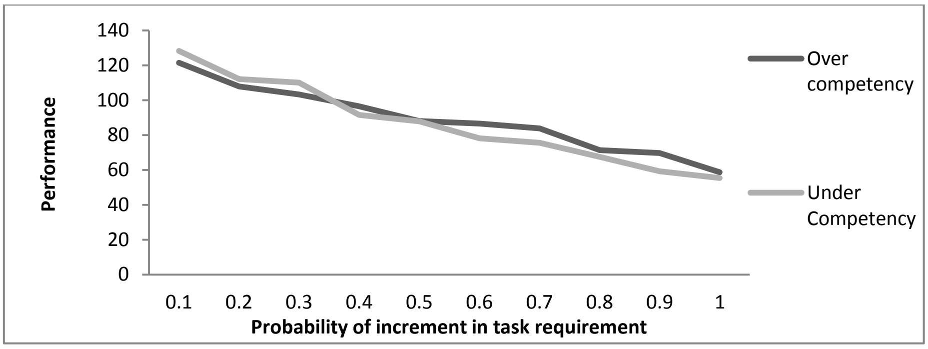

Fig. 2. Effect of task allocation mechanism on performance of tasks with dynamic requirements.

4.1 Relationship of Personality and Performance

In order to understand the relationship between personality and dynamic tasks, we conducted further simulation experiments. In the previous experiments, we assigned random personalities to the employees. In contrast, in these experiments, some scenarios are evaluated with respect to various personality configurations. We examined the performances of members with different distributions of personality when the probability of changing the requirements of the task in each time-step is 0.3. In other words, we are interested to examine whether a task allocation mechanism has any advantages over another one for a particular personality distribution. In order to assess the robustness of each personality distribution and qualify the certainty of predictions arising from experiments, we used a *one-at-a-time* uncertainty analysis technique, the Vargha-Delaney A-test [27].

In our experiments, we have 20 scenarios; each scenario represented a different personality distribution, and the results are summarized in Table 4. In each scenario, we measure the probability that the under-competency mechanism performs better than the over-competency mechanism.

For instance, the first number in the left-top of the Table 4 is 0.391. This number means in the case that 0% of employees are introverted, and 100% are extraverted the probability that under the competency mechanism performs better than over competency is 0.391.We found that the magnitude of the performance advantages depends not only on the personality distribution, but also on task allocation strategy. In most of the cases (different distribution of personality), there were none or only a small magnitude effect measured by the A-Test score between task allocation mechanisms. In most of the scenarios, the probability, of having a better performance with under-competency mechanism is slightly better than the other task allocation mechanism. However, we observed in some scenarios the over-competency mechanism outperformed the under-competency mechanism with a medium magnitude effect. For example, when 100 % of the employees have Judging type, the

A-score is 0.581, which means the probability that the over-competency performs better than under-competency is 0.581. In general, the over-competency mechanism had slightly better performances in cases when the majority of employees were Feeling or Perceiving or Sensing or Extraverted.

We can have approximate explanation for these observations. For instance, when the majority of employees are Extraverted, minimizing over competency more likely save some of the capability of the organization for the next projects with a high sociality requirement.

Table 3. The effects of different personality distributions in the comparison of the over-competency strategy with under competency strategy.

	I-E	N-S	T-F	P-J
0%-100%	0.391	0.53	0.578	0.312
25%-75%	0.432	0.522	0.504	0.366
50%-50%	0.476	0.513	0.451	0.397
75%-25%	0.493	0.43	0.424	0.492
100%-0%	0.545	0.37	0.405	0.581

5 CONCLUSION

In this paper, we have proposed a computational model, parameterized on the basis of reports in the academic literature, for measuring the performance of software teams considering their personality composition and skill competency. Based on this concept, we examine the effect of managers' strategies for task allocation on team performance when they are dealing with dynamic tasks. We ran agent-based simulations and designed various scenarios with different degrees of dynamic level. We studied whether a resource allocation strategy leads to performance advantages with respect to dynamic tasks. We also examined whether different personality distributions have an effect on two different task allocation methods. The effects of the personality distribution and the magnitudes of the impact of each personality were measured.

Based on these experiments, we drive a set of propositions about the conditions under which there are and are not performance benefits from employing a particular strategy for task allocation. Increasing the degree of changing requirements had a more adverse effect when the strategy of managers is minimizing under-competency compared to when the strategy of managers is minimizing over-competency. In addition, in most cases of the personality distribution, two strategies did not have significant differences; however, for a few scenarios some exceptions were observed.

We wish to note here that what we are presenting here as a contribution is not so much the specific simulation results, but a modelling and simulation approach that can demonstrate interesting emergent effects based on combinations of personality and skill configuration parameterizations. This parameterization can be set for the specific contextual circumstances to examine sensitivities in this area.

Our work would be enhanced by the availability of real data that could be used to validate the assumptions and the results. In the future, we will be gathering data concerning these tasks allocation mechanisms from groups of software engineering students undertaking group projects. Also, this system could be used to assist real managers to keep track of their task allocation activities. We intend to provide a decision-support system tool that employs our modeling approach to support managers' activities in dealing with dynamic tasks.

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